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Space and Time Modeling and Mapping Dengue Disease in Bali

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Abstract
Dengue disease is a mosquito-borne tropical disease caused by the dengue virus. The disease spread by mosquitoes vector. The weather factors are known as important factors affecting dengue transmission and the most important weather is precipitation. However, a lot of studies have a different result about the direction of the effect on the incidence. Some studies show the precipitation has positive and the other studies state the precipitation has a negative impact. The complex system relationship between dengue disease incidence and weather condition make some studies have a different conclusion. We use a spatial panel model to accommodate the spatial and temporal characteristics of dengue data in the model and apply the data on dengue disease in Bali province, Indonesia. We found the Spatial Autoregressive and Random Effect polynomial second order regression model is the best model. We found the heavy precipitation has a negative effect on dengue disease prevalence because the heavy precipitation may flush the breeding sites of mosquitoes.

Keywords: *Dengue disease, spatial panel, precipitation*

1. Introduction

Dengue disease is a mosquito-borne tropical disease caused by the dengue virus. It is rapidly spreading through female Aedes Aegypti mosquitoes [1] [2] [3]. More than 100 tropical and subtropical countries in Africa, Americas, and the Asia Pacific regions have been infected by dengue disease. People that is infected by dengue disease suffering from dengue fever experience sudden onset of fever, rashes, muscle aches, joint pain, and leucopenia [4]. The patient usually needs 14 days to hospitalize for recovering. if the patient is late getting treatment, dengue fever can cause death [5]. Around the world, about 500,000 severe dengue cases with 12,500 deaths have been reported annually [6]. Indonesia is one of the country in the south east Asia that has a serious problem with dengue incidence. In 2017, there were 59,047 number of incidences and 444 died [7]. Bali has reported the highest incidence rate since 2011, ranging from 65.90 per 100,000 population in 2012 to 484.02 per 100,000 population in 2016 [7]. Weather factors such as temperature, humidity, precipitation are important factors effecting dengue incidence [4]. Those weather factors impact dengue incidence by affecting adult feeding behavior, larvae development, and mosquito survival. Although mosquitoes require sufficient precipitation for breeding and larval development too much precipitation can reduce mosquitoes breeding site and reduce number incidences [4]. In this study, we focus on evaluating the space-time geographical variation of dengue prevalence related to the precipitation because some studies reported the different results of the effect precipitation on dengue incidence. Some research reported negative effect and the other studies reported positive effect.

Dengue disease prevalence have space-time characteristics, its prevalence may differ by space and time. To estimate the effect of precipitation on the dengue prevalence, we propose spatial panel data model which consider space-time dependcies. The structure of the remainder of this paper is as follows. Section 2 presents the material and method. Section 3 applies the method to Bali, Indonesia. Section 4 presents the conclusions.

2. Material and Method

Material

Materials area Bali province in Indonesia is a truism island located 8°20′06″S 115°05′17″E with land size of about 5,780 km^2. Total population in 2016 is 4.3 million with population density 750 $/km^2$. As a part of tropical country, Bali experiences high temperature, precipitation, and humidity year round. Highest precipitation between December and early March.

Data collection Monthly dengue cases from 2011 to 2016 were obtained from the Bali health profile (2012-2017) [1] [2] [3] [4] [5] [6]. Monthly cumulative precipitation recorded by the Bali meteorological for the period of 2011–2016.

Method

Without effective drugs or a vaccine, vector control remains the only method of controlling dengue fever outbreaks in Bali. Based on our previous findings on the effects of weather on dengue cases and optimal timing for issuing dengue early warning in Bali, the purpose of this study was to develop a dengue model that would provide early warning of a dengue outbreak several months in advance to allow sufficient time for effective control to be implemented. We constructed a statistical model using monthly cumulative precipitation.

Spatial Panel Model

Spatial panel models were developed to accommodate the spatial interaction between spatial units and over time. The general static panel model includes a spatial lag of the dependent variable and spatial autoregressive disturbance is given by [14]:

$$y = \rho(I_T \otimes W_N)y + X\beta + u \qquad (1)$$

where y is an $NT \times 1$ vector of observation on the dependent variable, X denote the matrix design a $NT \times K$ matrix of predictor, I_T an identity matrix of dimension T, W_N is $N \times N$ spatial weight matrix of known constant whose diagonal element are set to zero and ρ corresponding spatial autocorrelation parameter. In this study the dependent variable is dengue prevalence and the predictor was considered precipitation. The number location $N = 4$ and period $T = 72$. The error vector is the sum of two terms [14]:

$$u = (l_T \otimes I_N)\mu + \varepsilon \qquad (2)$$

where l_T denotes a $T \times 1$ vector of ones, I_N and $N \times N$ identity matrix, μ is a vector of time invariant individual specific effects (not spatially autocorrelated), and ε is a vector of spatially autocorrelated innovations, that follows a spatial autoregressive process of the form as:

$$\varepsilon = \lambda(I_T \otimes W_N)\varepsilon + v \qquad (3)$$

with λ ($|\lambda|$<1) as the spatial autoregressive parameter, $v_{it} \sim IID(0, \sigma_v^2)$ and $\varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2)$.
The individual effects can be assumed as fixed or random. Hence the model can be a fixed and random effects model. In fixed effect model we assume there is a differences the mean of dependent variable over space or time. In a random effect model, one is implicitly assuming that the unobserved individual effects are uncorrelated with the other explanatory variables in the model. In this case, $\mu_i \sim IID\left(0, \sigma_\mu^2\right)$ and the error term can be written as:

$$\varepsilon = (I_T \otimes B_N^{-1})v \qquad (4)$$

where $B_N = (I_N - \rho W_N)$. Hence, the error term u defines as:

$$u = (l_T \otimes I_N)\mu + (I_T \otimes B_N^{-1})v \qquad (5)$$

and the variance-covariance matrix for ε is given by:

$$\Omega_u = \sigma_\mu^2(l_T l_T' \otimes I_N) + \sigma_v^2[I_T \otimes (B_N' B_N)^{-1}] \qquad (6)$$

To estimate the space-time models by means spatial panel models we use splm R-package [14]. It is the most important package for analysis space-time data in econometrics modelling.

3. Results

During the study period, the heaviest precipitation occurred in April and dengue disease prevalence occurred in January. The descriptive statistic of precipitation and dengue disease prevalence rate is given in Table 1.

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Table 1. Descriptive statistic of prevalence and precipitation by district

District	Average of Prevalence	Average of Cumulative Precipitation
Kabupaten Badung	0.029	153.296
Kabupaten Jembrana	0.009	149.029
Kabupaten Karangasem	0.017	155.728
Kota Denpasar	0.018	152.747
Mean	0.018	152.700

Table 1 shows the prevalence rate of Kabupaten Jembrana is lowest compare than the other districts and the highest prevalence rate is found in Kabupaten Badung.

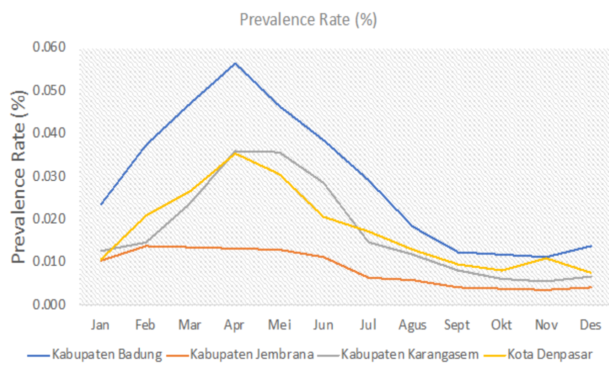

Figure 1. Prevalence rate by time and district

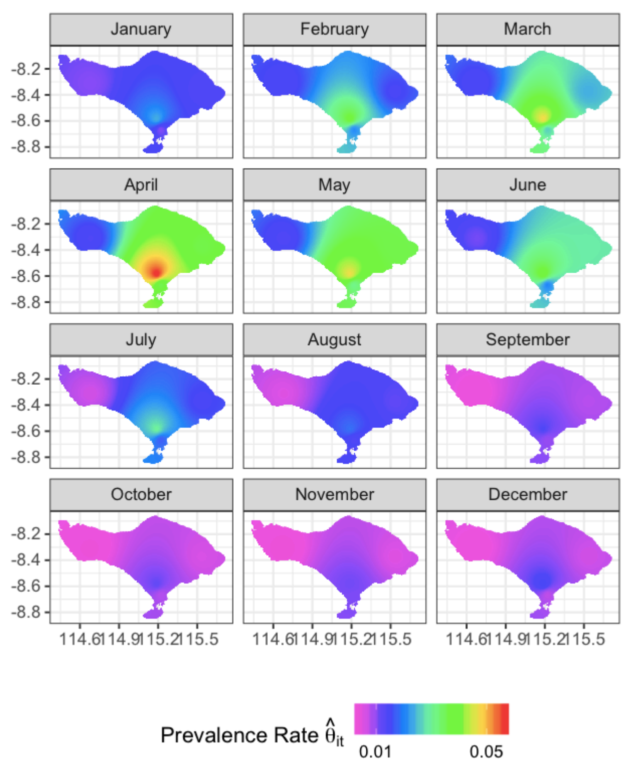

Figure 2. Space time of prevalence rate

Figures 1 and 2 show the space-time prevalence rate. Figure 1 shows clearly the time pattern of prevalence rate for district Kabupaten Badung, Jembrana, Karangasem and Kota Denpasar. Figure 2 clearly presents the space-time geographical variation of dengue disease prevalence in Bali province. The high prevalence rate was found around the period from January to June. After June, the dengue prevalence rate was getting low.

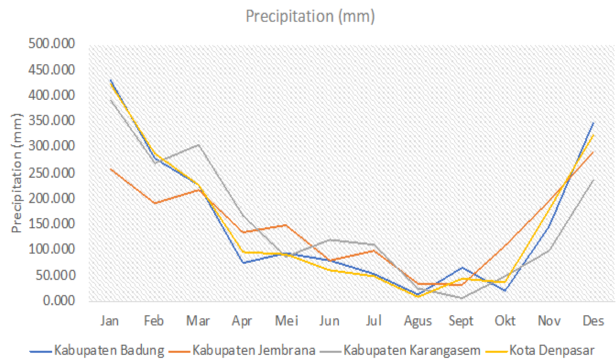

Figure 3. Cumulative monthly precipitation by time and district

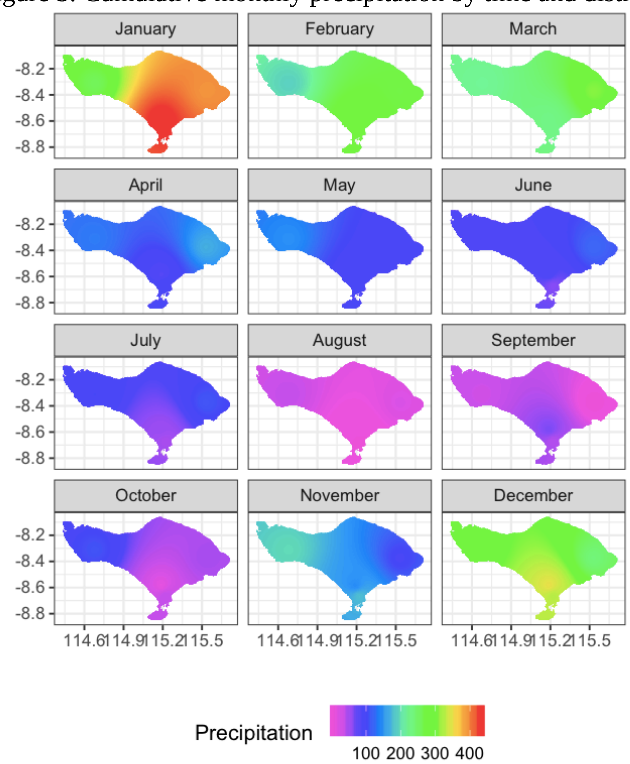

Figure 4. Space time of precipitation

Figures 3 and 4 show the space-time precipitation. Figure 3 shows clearly the time pattern of precipitation for district Kabupaten Badung, Jembrana, Karangasem and Kota Denpasar. Figure 4 clearly presents the space-time geographical variation of precipitation in Bali province. The high prevalence rate was found around the period from December to March. After June, the dengue precipitation was getting low.

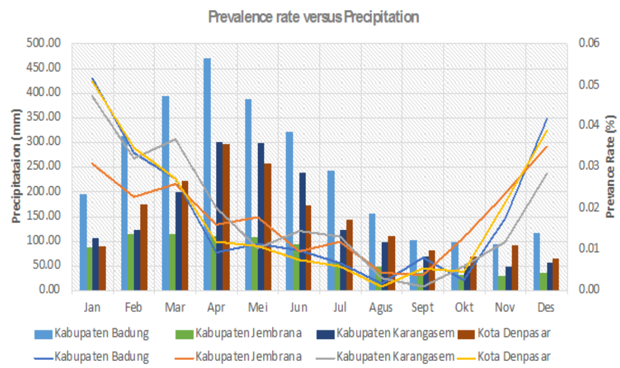

Figure 5. Prevalence versus precipitation

Figure 5 shows the prevalence rate and precipitation. A similar pattern is shown for the period from March to October. Decreasing precipitation is followed by a decreasing prevalence rate. However, there is a strong different pattern between dengue disease prevalence for the period November to February. It makes difficult to decide the relationship between precipitation and prevalence rate [7] dengue disease in Bali. Next, we present the linear and nonlinear quadric plot in Figure 6 and Figure 7.

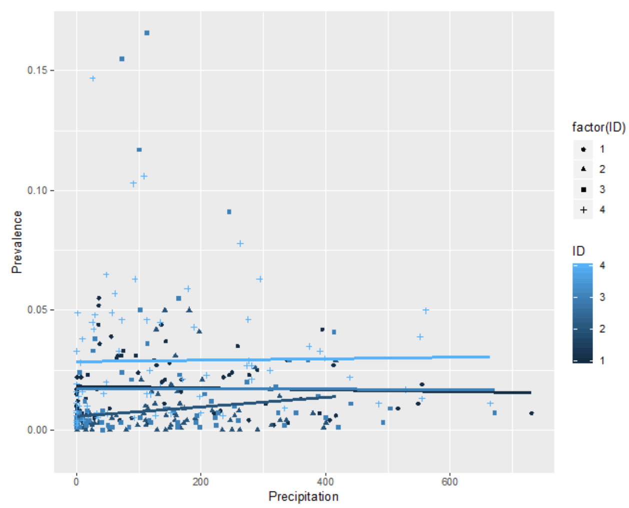

Figure 6. Linear trend of precipitation on prevalence rate

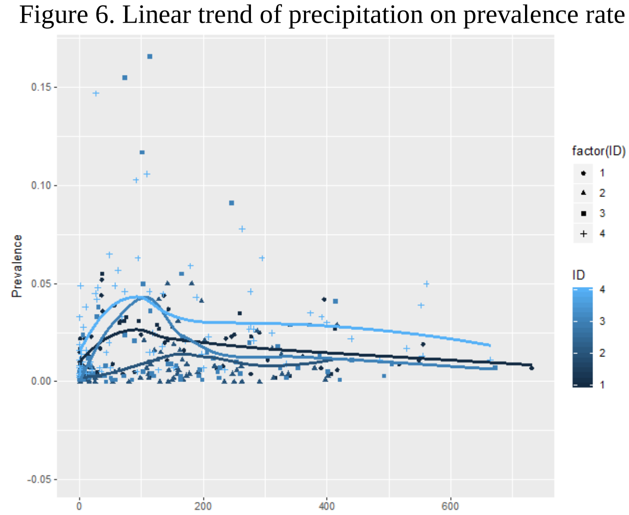

Figure 6. Nonlinear trend of precipitation on prevalence rate

Given both figures, Figure 6 seems more accurate to predict dengue prevalence compare to Figure 5. To prove this hypothesis we estimate the linear and nonlinear models are given in Table 2 and Table 3.

We consider the spatial panel quadratic model by assuming the square of precipitation indicates the heavy precipitation. If the square of precipitation has a significant effect on dengue prevalence, it proves that the heavy precipitation will reduce the number of incidence by reducing the mosquitoes breeding.

The space-time models are estimated using the maximum likelihood estimator and tested by asymptotic normal.

Table 2. Linea model

Model	β_1	p-value	Spatial Autocorrelation	p-value
SAR-Pooling	-3.96E-08	0.891	0.515	<2e-16 ***
SAR-Fixed	-9.04E-07	0.884	0.581	<2e-16 ***
SAR-Random	-8.60E-07	0.891	0.578	<2e-16 ***
SEM-Pooling	-3.74E-06	0.507	0.516	<2e-16 ***
SEM-Fixed	-6.61E-06	0.499	0.583	<2e-16 ***
SEM-Random	-6.53E-06	0.507	0.582	<2e-16 ***

Table 2 shows the parameter estimate of spatial panel models including SAR-Pooling, SAR-Fixed Effect, SAR-Random effect, SEM-Pooling, SEM-Fixed effect, and SAR-Random effect. All the models have significant effects of spatial autocorrelation of lag dependent and error dependent. However, the linear effect of precipitation of all models is not significant. It indicates that the precipitation does not have a linear effect on dengue disease prevalence. Next, we apply nonlinear model using model quadratic with the results are presented in Table 3.

Table 3. Nonlinear model

Model	β_1	β_2	p-value β_1	p-value β_2	Spatial Autocorrelation	p-value
SAR-Pooling	5.05E-06	-1.06E-08	0.793	0.776	0.513	<2e-16 ***
SAR-Fixed	2.68E-05	-5.75E-08	0.115	0.080*	0.573	<2e-16 ***
SAR-Random	2.58E-05	-5.54E-08	0.131	0.094*	0.570	<2e-16 ***
SEM-Pooling	-3.05E-05	5.15E-08	0.227	0.244	0.528	<2e-16 ***
SEM-Fixed	8.95E-06	-2.98E-08	0.70	0.462	0.579	<2e-16 ***
SEM-Random	6.70E-06	-2.53E-08	0.774	0.534	0.579	<2e-16 ***

*) significant at level 0.1.

Apply the quadratic model we obtain extremely different results with a linear model. In the linear model, all the slop regression for precipitation variable has negative signs. Here for the quadratic model, the slop regressions for all linear effect is positive except for SEM-Pooling effect. The sign of regression coefficients of the quadratic variable is negative except for SEM-Pooling. Here we found the are two models where the coefficient of the quadratic variable has a significant effect on level significant 0.1. The models are SAR-fixed and random effect models. It indicates there is a negative effect of quadratic precipitation on the dengue disease prevalence in Bali province. To choose the best model between fixed and random we use Baltagi, Song and Koh SLM1 and LM2 [7] test which is given in Table 4 .

Table 4. Model evaluation

Baltagi, Song and Koh SLM1 marginal test data: Prevalence ~ Precipitation + I(Precipitation^2) LM1 = 9.8187, p-value < 2.2e-16 alternative hypothesis: Random effects Baltagi, Song and Koh LM2 marginal test

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data:  Prevalence ~ Precipitation + I(Precipitation^2)
LM2 = 10.753, p-value < 2.2e-16
alternative hypothesis: Spatial autocorrelation
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Given the model evaluation in Table 4 using Baltagi, Song and Koh SLM1 and LM2 marginal test we select the best model is Spatial Autoregressive Random Effect model (SAR-RE). This model indicates there is no signfincant different prevalence for every district however, there is a variation between prevelence of each district .

4. Conclusion

Precipitation is already known as the most important weather factors effecting to dengue incidence due to its contribution to mosquitoes live cycles [1] [2]. The precipitation provides stagnant water pools which are useful to reproduce of mosquitoes [3]. However, heavy precipitation may flush out these breeding sites and make the larvae death. It is potential to reduce the adult mosquitoes in the following weeks [4]. These condition makes difficult to model precipitation on dengue incidence or prevalence.

To estimate the relationship between precipitation on dengue prevalence in Bali province, we consider the spatial panel model because we believe that the dengue prevalence has spatial and temporal characteristics. The spatial panel model evaluates the monthly precipitation. The peak of monthly precipitation occurs around April and May for all regions in Bali. The dengue prevalence also seems high in those periods, however the peak around January and February.

Using a spatial panel model and we found the best model is the Spatial Autoregressive Random Effect model (SAR-RE). The model informs there is a strong and significant spatial autoregressive coefficient and the square of precipitation has a negative significant impact on dengue prevalence. It supports that the heavy precipitation flushes out the breeding sites and makes the larvae death, therefore reduce the adult mosquitos and might leads to the decreasing dengue disease incidence for all districts in Bali province.

Although we found the heavy precipitation has a negative impact on dengue prevalence, the light precipitation for a long time period may have a positive effect on dengue prevalence because of the light precipitation will provide the stagnant water pools which are useful for mosquitoes to breed. Hence, it is important to clean the stagnant water pools to cut the mosquitoes' life cycles.

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